Experiencing and Handling the Diversity in Data Density and Environmental Locality in an Indoor Positioning Service

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ABSTRACT

Diversity in training data density and environment locality is intrinsic in the real-world deployment of indoor localization systems and has a major impact on the performance of existing localization approaches. In this paper, through micro-benchmarks, we find that fingerprint-based approaches are preferable in scenarios where a dense database is available; while model-based approaches are the method of choice in the case of sparse data. It should be noted, however, that practical situations are complex. A single deployment often features both sparse and dense sampled areas. Furthermore, the internal layout affects the propagation of radio signals and exhibits environmental impacts. A certain number of measurement samples may be sufficient for one part of the building, but entirely insufficient for another. Thus, finding the right indoor localization algorithm for a given large-scale deployment is challenging, if not impossible; there is no one-size-fits-all indoor localization approach.

Realizing the fundamental fact that the quality of the location database capturing the actual radio map dictates localization accuracy, in this paper, we propose Modellet, an algorithmic approach that optimally approximates the actual radio map by unifying model-based and fingerprint-based approaches. Modellet represents the radio map using a *fingerprint-cloud* that incorporates both measured real fingerprints and virtual fingerprints, which are computed from models with a local support, based on the key concept of the *supporting set*. We evaluate Modellet with data collected from an office building as well as 13 large-scale deployment venues (shopping malls and airports), located across China, U.S., and Germany. Comparing Modellet with two representative baseline approaches, RADAR and EZPerfect, demonstrates that Modellet effectively adapts to different data densities and environmental conditions, substantially outperforming existing approaches.

Categories and Subject Descriptors

C.2 [**Computer-Communication Networks**]: Miscellaneous

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Keywords

Indoor Localization; Fingerprint; Model

1. INTRODUCTION

In recent years, indoor localization has been one of the most deeply and frequently studied problems both in the mobile computing research community, and in industry (over 90 companies now in the indoor localization alliance [3]). WiFi-based indoor localization approaches have been the center of attention, due to their low deployment cost, potential for reasonable accuracy and readiness to be applied to mobile devices. Existing WiFi-based solutions usually fall into one of two categories: fingerprint-based [5, 20, 40] and model-based approaches [9, 11, 15, 23]. The former fingerprints locations in the area of interest and then searches for the best matching location, while the latter trains a signal propagation model using training/calibration data and then applies trilateration for localization. While these methods have been shown to achieve promising localization accuracy (below 10 meters at 90%tile) under lab conditions, large-scale accurate indoor localization systems have yet to be developed. For example, given real-world fingerprint sampling conditions, the localization accuracy of existing approaches in large venues like shopping malls and airports can still be up to 20∼30m at 90%tile; similar results are reported by Google [2].

One reason for this well-known and frequently-lamented discrepancy is that academic research has so far mostly focused on only one part of the problem: location inference, i.e., resolving the position for a given WiFi signal. However, for any given location inference algorithm, it is how well the location database captures the actual radio map that dictates localization accuracy. Thus, it is crucial to acquire (and maintain) a high-quality database.

In our experience with over 13 large-scale industrial deployments, we have found that the challenges lie in both data density and environmental conditions. It is often difficult, if even possible, to obtain an equally dense set of high-quality samples across an entire building complex. And even if it was possible to get a spatially uniform sample database (in some subareas), the different local environments (room layout, AP deployment, etc) imply that the sampled fingerprints may yield high-accuracy localization in one location, while being entirely insufficient in others. Such reality poses a fundamental challenge to existing WiFi-based indoor localization approaches, partially explaining their inadequate performance in practice. A key insight suggested by this study is that different localization approaches are preferably applied under different conditions (data density, environment); for a given approach, parameters should be fine-tuned for different locations within the same deployment. In other words, there is no one-size-

fit-all solution among existing localization algorithms, even for a single deployment. Such a conclusion is also implicitly supported by observations from [6, 12], in which the authors did extensive measurements and experiments in a lab setting.

In this paper, we set out to attack the challenges of nonuniform data density and environmental impact by designing a systematic and unified way to better approximate the actual radio map using whatever data samples are available. We propose *Modellet*, an algorithmic approach that optimally approximates the actual radio map by unifying a model-based and fingerprint-based approach.

Inspired by the practice of visualizing a surface through meshing neighboring vortexes in computer graphics, in Modellet, we try to approximate the possibly irregular radio map by 'meshing' neighboring fingerprints. In particular, Modellet adapts to the specific local data density and environmental conditions by fusing information from both measured fingerprints and signal propagation models, based on the key concepts of the *supporting set*. A supporting set is a set of real fingerprints from which a derived model can best approximate the local radio map. Borrowing from the practice of using point cloud to represent arbitrary object in 3D modelling, we propose a *fingerprint-cloud* notion to approximate the actual radio map, i.e., representing arbitrary shaped radio map from dense fingerprints. A fingerprint-cloud incorporates both real and virtual fingerprints, where virtual fingerprints are spatially uniformly sampled across areas of interest and computed via the signal propagation model obtained from the supporting set.

The combination of fingerprint-cloud and supporting set enables Modellet to always adjust to the locally optimal trade-off between model-based and fingerprint-based approaches, and to optimally fine-tune the algorithm parameters. An effective device gain estimation method is also proposed to address device diversity. As a result, Modellet performs well under real-world noisy and nonuniform datasets, and in different environmental conditions. We are aware that several previous studies have examined localization accuracy against various data densities and environmental conditions, like [5, 6, 12, 17, 26] among others. However, to the best of our knowledge, we are the first to try designing a systematic approach that automatically adapts to data density, which may change as more data flows in.

In summary, we make the following major contributions:

- We establish how different families of localization algorithms perform differently under different data densities and environmental conditions. To the best of our knowledge, this is the first in-depth study in this field.
- We design a unifying localization framework called Modellet, which addresses the challenges of nonuniform data density and environmental impacts from a database construction aspect. Using the concept of fingerprint-cloud and supporting set, Modellet ensures an optimal use of available sample data in the vicinity of the location in question. An effective device gain estimation method is also proposed.
- We conduct extensive experiments based on real data collected from an office building and over 13 large venues, located in China, US, and Germany. Such large-scale evaluations for indoor localization using realistic databases have rarely been published.

The paper is organized as follows: Section 2 describes the motivating observations regarding data density and environmental conditions. We provide the overview of Modellet in Section 3, followed by details on its core concepts in Sections 4 and 5. We further present a way to address the device gain diversity in 6. We evaluate Modellet in Section 7. We discuss practical issues and possible extensions in Section 8 and provide an overview of existing the state-of-the-art indoor localization methods in Section 9. Section 10 concludes this paper.

2. MOTIVATION

2.1 Properties of Real Service Data

We conduct real world deployments of indoor localization services at multiple large shopping malls, airports and enterprise buildings. The large scale real world training data collected during such deployments reveals two features that do not stand out from those collected in a lab environment in early research papers.

Nonuniform Data Density: The data we obtained, through both war-walking and tap-and-point methods of data collection by third-party vendors, are of different density across different subareas of various indoor environments. For example, the pathway areas usually have much denser training data than the inner parts of the shops in a mall. There are many reasons for the surveyor cannot perform long time data collection inside shops without getting consent from the shop owner; it is more challenging to figure out precise positions within shops than on the pathways as the maps contain little information about inner shops; pathways can be surveyed by regular walking while inside shops have to be collected point by point. The situation will not change substantially for crowdsourcing-based data collection (e.g., [22, 31, 33, 38]) as popular places and pathways will always have more chances to be visited and hence enjoy more frequent data collection. In addition, the WiFi infrastructure may be updated with APs removed, relocated or added. Thus, it is unlikely to obtain a location database that has all indoor areas sampled dense enough and up to date.

Environmental Impact: Indoor environments are typically divided into many smaller functional areas such as corridors, rooms and shops, among others. They are usually separated using cement, wood or glass walls that cause different penetrations and reflections of radio signal. Unlike office or campus building environments, shopping malls and airports are usually constructed very differently. Their internal layouts are much less regular and may be arbitrarily divided to meet different functional requirement. In particular, shopping malls and airports often contain large atria. This renders them very challenging environments for indoor positioning. Signals from multiple floors can be heard at locations near the atrium. It is difficult even to locate user's correct floor.

2.2 Impact on Localization

To understand how training data density and environmental conditions may affect localization accuracy, we carry out several microbenchmarks to understand their impact. In our experiments, we consider RADAR [5] and EZPerfect [9, 28], which are representative fingerprint-based and model-based localization approaches, respectively.

- **RADAR** first collects fingerprints from various known locations to build up a fingerprint database. It then determines the position of an incoming fingerprint by comparing it against all fingerprints in the database, and averages the locations of a few fingerprints nearest in signal space.
- **EZPerfect** adopts the log-distance path loss (LDPL) model [28] and trains model parameters from fingerprints with known locations. Model parameters instead of fingerprints are stored in the location database. Trilateration or multilateration is applied to estimate the location for an incoming fingerprint.

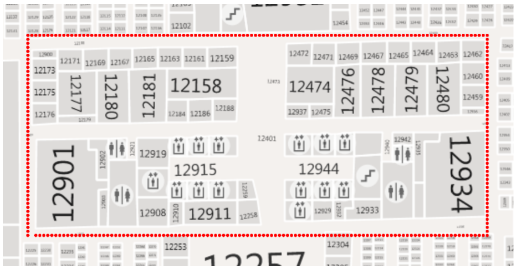

Figure 1: A $75m \times 40m$ office area for data collection. Each red dot represents a sampling location. One fingerprint is collected for each location.

Horus [40], a proven approach that outperforms RADAR, was not considered here. Horus achieves excellent performance by exploring temporal diversity (i.e., repeated sampling at the same location) to iron out random errors in signal readings. However, the data collection time is prohibitive in real world deployment. Even with war-walking based data collection, venues like large shopping malls in our evaluation in Section 7 still require a whole day (around 8 hours) to fill each $10 \times 10m^2$ grid only $20 \sim 30$ fingerprints, far below the number of samples (100) per $1 \sim 2m$ apart adopted in [40].

The data for our benchmarks was densely collected along the corridors in an office building, as shown in Fig. 1. Fingerprints are collected $\sim 0.6m$ apart, producing a total of 329 fingerprints. The high data density allows us to emulate sparser data collection via downsampling. As corridors have much simpler structure than other areas such as inner shops, we expect the findings below would be more severe for other indoor areas.

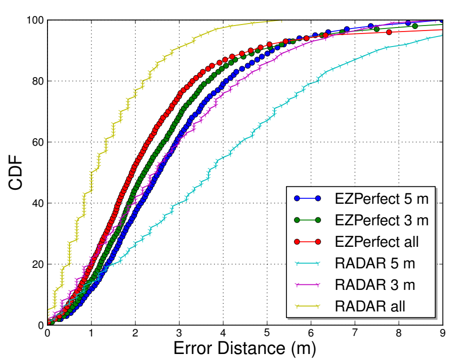

Figure 2: Localization errors at different data densities, for RADAR and EZPerfect. '3m' and '5m' are the grid size for downsampling, and 'all' means using all the data.

Impact of Data Density: We first split the whole dataset into training (80%) and testing (20%) data. Then, we vary the density of the training data by uniform downsampling. Fig. 2 shows the comparisons between RADAR and EZPerfect under various data densities. In the figure, '3m', '5m' and 'all' means retaining one sample every 3 meters, one sample every 5 meters and using all samples, respectively. We can see that EZPerfect outperforms RADAR on downsampled data, while RADAR achieves better accuracy with full data. Thus we make the following observation:

Observation 1: Fingerprint- and model-based approaches are more suitable for different densities. With dense training data, fingerprint-based schemes yields better accuracy; whereas with sparse training data, model-based ones are better.

As indoor location services may obtain new training data over time, e.g., through additional surveys or contributions of real users, the density of training data may vary. The above observation implies that the location service should be able to automatically adapt to and make best use of all available training data. A similar observation is made in [6], where the authors experiment with different number of sniffers (called landmarks) to locate one transmitter and found different sniffer densities favor different localization methods. The difference with our observation lies in that ours is made from varying densities of collected fingerprints.

Impact of Environmental Conditions: To show how the physical layout of indoor environment affects indoor localization, we highlight in Fig. 3 the measured RSSs and the model fitness errors for a randomly picked AP. Here, the fitness error refers to the difference between the measured and model-calculated RSSs. In the left figure, a bubble stands for an observation. The size and color of the bubble represent the magnitude of RSS: the larger and the redder the bubble, the higher the RSS, and vise versa. We can see that the signal attenuates at very different speed along different corridors. For instance, positions A and B are the same distance from the AP, but their RSSs differ by 10dB. In the right figure, bubble size indicates the magnitude of fitness error, and the green or blue color stands for a positive or negative error. From the figures, we make the follow observation:

Observation 2: The internal layout of an environment significantly impacts radio signal propagation. Applying a single omni-model to all observations always yields large fitness errors. Yet nearby positions tend to see a similar fitness error, which indicates the existence of environmental locality.

Note that the environmental impact is orthogonal to the training data density. No matter how dense the data is, the environmental impact persists.

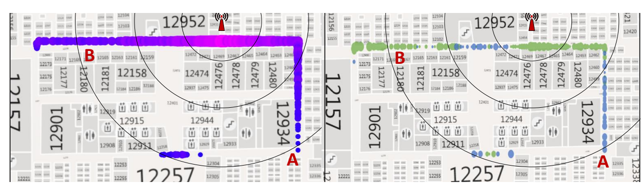

Figure 3: The observed RSSs and model fitness errors of a randomly picked AP along the corridors.

Observation Analysis: The above observations are rooted at the irregularity of a *radio map* – a map of signal strengths at different locations, and the ability to approximate the radio map from training data. The localization process is actually a process to find the best match(es) to a given fingerprint from the radio map and return the position of the best match(es). The better we can approximate the actual radio map, the better the localization accuracy that can be achieved.

When the training data are sparse, the radio map cannot be well approximated with few fingerprints. However, under the assumption of a radio propagation model, the radio map can be better approximated. The model requires only a few samples to train the model parameter. On the contrary, when the training data are dense, distances between fingerprints are close. Thus, direct use of the fingerprints can well approximate the radio map, whereas an oversimplified omni-model will lead to a high fitness error.

The second observation is easy to understand. The walls block or alter the radio signal propagation paths. An overall omni-model must be a compromise between all observations, and nearby positions in the area warded by same walls tend to have a similar model fitness error.

Though our observations are based on two specific localization schemes, i.e., RADAR and EZPerfect, the above analysis can be generalized to the whole class of solutions. Fingerprint based approaches approximate the radio map with nonparametric models. Thus, they essentially require dense data for better approximation, due to lack of knowledge in between measurements. On the other hand, omni-model based solutions use an oversimplified signal propagation model to fit the measurements, leading to underfitting under a dense database.

2.3 Simple Hybrid Does Not Work

The above analysis suggests that a simple hybrid of fingerprint-based and model-based solutions may automatically adapt to various data densities. There may be different hybrid versions. An intuitive method could be to switch between the two approaches depending on data density. i.e., if the data density is higher than the threshold, we use a fingerprint-based approach, otherwise, we choose a model-based approach. However, it is nontrivial, if not impossible, to find this optimal threshold across various areas. Motivated by observation 2, a second approach is to apply a fingerprinting approach in complex areas and apply a model-based approach in large and open areas such as [18,21]. However, they all rely on the assumption of knowing the exact information of the wall (material and thickness) and AP (power and position). Unfortunately, such an assumption is generally unrealistic. A third method is to first apply fingerprinting and obtain a few top candidates with which a model is then trained from the resulting candidates. This approach, however, is dictated by the accuracy of the candidates returned from fingerprinting.

2.4 Challenges Towards Real World Services

Microbenchmarks and analyses reveal that the following challenges and requirements regarding the best use of training data ought to be addressed to provide high accuracy indoor localization services.

- Nonuniform data density. The system should be able to automatically adapt to training data densities, sparse to dense, which may even be altered over time.
- Environmental locality. The system should explore the environmental localities in an autonomous way, without the assumption of any priori knowledge of actual layout.

In addition, the well-known RSS fluctuation problem and device diversity problem (i.e., different devices or the same device at different battery levels may have different receiver gain) have to be tackled as well.

3. MODELLET OVERVIEW

We set out to attack the challenges of nonuniform data density and environmental locality through the design of a systematic and unified way to better approximate the actual radio map. We further handle the device diversity problem through a dedicated device gain estimation process.

3.1 Concepts in Modellet

As a thought process, if we think of the radio map as an unknown, possibly irregular surface, the task of approximating the radio map is then to reconstruct the surface from observations contained in the training fingerprints. Inspired by the practice of visualizing a surface by meshing neighboring vortexes in computer graphics, we may also mesh the neighboring fingerprints to approximate the radio map.

Supporting Set: Directly meshing neighboring fingerprints is improper as it implies a simple linear interpolation for positions in between. The radio map produced in this way would be very noisy due to RSS fluctuations and exhibits of discontinuity across mesh boundaries. To work around this, we incorporate *local models*. The intuition is simple: while one omni-model does not work well for the entire area under the AP's coverage, good local models still exist in smaller subareas. Therefore, if we can properly divide AP's coverage into small zones, we can better approximate the radio map using zonal models.

Clearly, the central task is to identify proper surrounding fingerprints, termed as a *supporting set*, in the proximity of any *location of interest*. The term location of interest, through out this paper, is referred to as the location whereas we predict its received signal strength from surrounding APs. Local models can then be built from the supporting set. Fig. 4 illustrates the supporting set for a location of interest (green circle) for a certain AP. While not showing, we point out that the supporting set for different APs and different interested positions will be different.

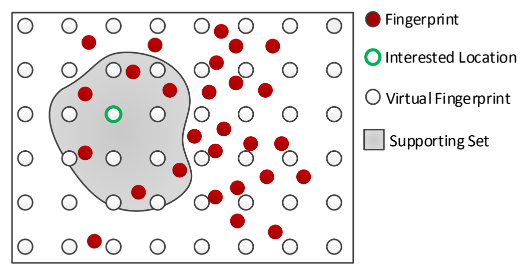

Figure 4: Conceptional illustration of the key concepts in Modellet. The supporting set includes only measured fingerprints (red dots). A virtual fingerprint may be at any position of interest.

The supporting set concept allows us to effectively explore environmental locality. In addition, as the number of parameters of the model is fixed (e.g., four parameters for LDPL model), the size of the supporting set is thus also limited, even though we usually adopt more fingerprints than necessary to iron out RSS fluctuations. This implies that the supporting set, and hence the local models and the resulting approximation to the radio map, is able to adapt to varying training data densities. The denser the training data, the more local (i.e., smaller spatial coverage) the supporting set. We elaborate the decision of supporting set and its adaptation mechanism in Section 4.

Fingerprint Cloud: It is infeasible to represent the radio map directly using supporting sets or corresponding derived local models. For any position of interest, a proper supporting set can be identified and hence a local model can be built for any AP that can be heard at that position. While the models of nearby positions will be the same if their supporting sets are identical, the number of potential supporting sets (hence models) of an AP may still be large. In addition, a real radio map usable for indoor localization consists of the maps of all APs. Due to different AP positions and their intersections with the physical layout, the supporting sets for different APs at the same position of interest are usually different.

To effectively represent the radio map, we propose the *fingerprint-cloud* (FP-Cloud) concept, which is borrowed from the point-cloud

used in 3D modeling. Just like point-cloud represents arbitrary shaped 3D models directly with dense sampling points, we capture the irregular radio map using *dense* fingerprints. As the actually collected fingerprints may not be dense enough, we create *virtual fingerprints* (VFPs) at positions that were not sampled, or more specifically at the locations of interest. Fig. 4 shows the FP-Cloud of a subarea where the white circles and red circles indicate the positions of virtual and real fingerprints, respectively.

Like a real fingerprint, a VFP also consists of a list of BSSID and RSS pairs annotated with a given location. The difference is the RSSs in VFP are calculated using the local signal propagation model (detailed in Section 5) whereas they are derived from real fingerprints. Evidently, incorporating both real and virtual fingerprints, FP-Cloud captures information from both real measurements and local signal propagation knowledge.

3.2 Modellet System Overview

The overall system architecture of Modellet is shown in Fig. 5. Similar to other indoor position systems, Modellet also consists of an offline database (FP-Cloud) construction process and an online location inference process. To generate the FP-Cloud, a venue is first surveyed by cite survey specialists or crowdsources to obtain training data. The training data is directly incorporated into the FP-Cloud as raw fingerprints. The positions of virtual fingerprints (VFPs) are then determined as locations of interest. For each location of interest, the supporting set is identified. The VFP is then generated by obtaining and applying the local model from the fingerprints in the supporting set. VFPs are stored in the FP-Cloud.

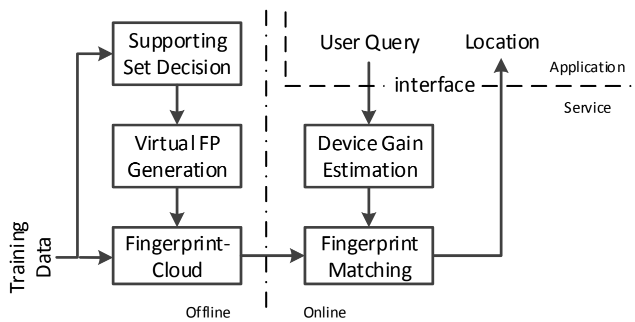

Figure 5: The Modellet system architecture.

In the online phase, upon receiving a query fingerprint, a device gain estimation process is executed. The estimated device gain and the user fingerprint are fed to the fingerprint matching engine, which returns the most likely location for the user query. Note that many location inference algorithms may be applied here. For instance, RADAR finds the K nearest neighbours (KNN) based on the signal strength vector distance, and uses the averaged location. EZPerfect uses trilateration to calculate one location minimizing the aggregated error distances to all APs. Even stochastic methods can be used [20, 40]. In our implementation, we use KNN as RADAR does.

4. SUPPORTING SET

The primary purpose of identifying the supporting set is to obtain a local model to better approximate the local surface of the radio map. A proper supporting set should also adapt to the training data density, and thus should be data-driven. When more data is available, the supporting set should be more concentrated.

4.1 Spatial Kernel Function

Rigid schemes (e.g., always selecting a certain number of fingerprints nearest to the position of interest) should be avoided even though they also adapt to data density. For rigid schemes, if a small number is set, they are not robust to RSS fluctuations; whereas if a large number is set, they may fail to identify a valid supporting set when data is sparse. Also, when the density is high, they may lead to underfitting.

In Modellet, we avoid hard decisions in identifying the supporting set. Instead we allow a large range of fingerprints to contribute but assign higher weights to fingerprints closer to the location of interest through a spatial kernel function.

Consider a set of n observations for a certain BSSID

$$S = \{s_1, s_2, \cdots, s_n\}$$

The goal is to estimate the RSS at a certain location of interest based on S through the local model. Let d_i be the Euclidean distance from the location of interest to the i^{th} observation s_i. We set the weight of s_i as a function of d_i, denoted as $w_i = K(d_i)$ where $K(\cdot)$ is a kernel function which is monotonously decreasing with d_i. We compared various kernel functions such as uniform, tri-cube, and Gaussian, and finally pick the normalized Gaussian for its robustness over signal fluctuations. Our kernel function thus looks like

$$K(d) = e^{(d_{min}-d)/k} \quad (1)$$

where k is called *bandwidth* which controls the impact of locality, and d_{min} is the distance from the location of interest to the closest observation among S. When $k \to \infty$, all measurements are assigned weight 1, which implies no impact from locality. We decrease the value of k to make it more biased for observations in proximity. One special case is that all observations in S are far from the location of interest, leading to small weight for all observations. We carry out normalization ensuring the weight of the observation closest to be 1.

In Modellet, we adopt the widely used log-distance path loss (LDPL) model [9, 15, 23], described as follows:

$$RSS_{x,y} = P_0 - 10\gamma \log d_{x,y} \quad (2)$$
$$d_{x,y} = \sqrt{(x_0 - x)^2 + (y_0 - y)^2}$$

where P_0 and γ are the reference power and path loss constant, respectively. (x_0, y_0) is the 2D location of the AP.

The parameters, namely P_0, γ, x_0, and y_0, are learnt from the observations in the supporting set, as in [9], with the difference being the minimizing of the aggregated *weighted* fitting errors, defined in the following equation:

$$E = \sum_{i \in [1,n]} w_i \cdot |s_i - \hat{s}_i| \quad (3)$$

where $\hat{s}_i$ is the calculated RSS with the the learnt LDPL model. Optimization is conducted using Gradient Descent in our implementation to minimize Eq. (3) in order for a set of parameters for a BSSID.

4.2 Finding The Optimal Kernel Bandwidth

A key parameter of the kernel function is the bandwidth, i.e., k in Eq. (1). As discussed above, a k that is too large eliminates the impact of locality, while one that is too small may cause overfitting to observations. Therefore, the goal of finding the optimal kernel bandwidth is: if one model fits the signal attenuation well, the supporting set should be large (i.e., large k), and vice verse (i.e., small k).

We develop a modified leave one out cross validation (LOOCV) for optimal kernel bandwidth selection. LOOCV is widely used for kernel bandwidth selection, especially with limited training data size. The process is purely driven by data. The conventional LOOCV is more suitable for homogeneous data, whereas a global optimal kernel bandwidth is selected. However, the signal propagation in an indoor environment is actually heterogeneous (hence the locality). Intuitively, for open areas where the signal attenuates smoothly, it is better to use larger bandwidth values for robustness against random signal strength fluctuations. In contrast, small bandwidth values should be used for locations where the signal strength varies more significantly.

Our modified LOOCV searches an optimal kernel bandwidth for each location of interest. There are two phases:

- Given a set of n observations $s_i, i \in [1, n]$, we carry out n rounds. In the i^{th} round, we use s_i for validation and the rest $n-1$ for training. We iterate k_i in a certain range (like $[1, 30]$), and find the one that minimizes the validation error $|s_i - \hat{s}_i|$. After n rounds, we derive a set of optimal kernel bandwidths $k_i, i \in [1, n]$, each corresponding to an observation.

- For each location of interest, we infer its kernel bandwidth based on the kernel bandwidths of nearby observations derived from the previous phase. Specifically, we adopt the mean kernel bandwidth of the top few nearest observations.

An underlying assumption here is that the kernel bandwidths of nearby locations are similar, which is implied by our observations in Section 2.

4.3 Effectiveness Verification

So far, we have discussed how to find an appropriate bandwidth for each location of interest. Figure 6 shows the signal strength heat map estimated for a certain AP using uniform (i.e., global, not using supporting set) and locality-aware LDPL models using supporting set, respectively. For uniform models, we basically set the weight of all observations to 1. We evaluate the localization accuracy of using uniform and locality-aware LDPL models with EZPerfect and RADAR. The results are shown in Fig. 7 and 8. One can see FP-Cloud with uniform models always outperforms EZPerfect and RADAR. By using locality-aware models, the gain further increases. Fig. 9 highlights the gain of using locality-aware models ($2.5m$ at 90%tile) over with uniform models ($3.5m$ at 90%tile), which is significant. Hereafter in our experimentation, Modellet always refers to FP-Cloud with locality-aware models.

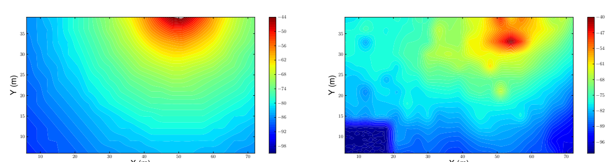

Figure 6: The heat map of signal strengths of the AP calculated with uniform (left) and locality-aware (right) LDPL models.

5. FINGERPRINT CLOUD

In essence, FP-Cloud is to use discrete fingerprint samples to approximate the continuous radio map. Shaped by the actual physical layout, the radio map can be highly irregular. Therefore, a certain density is necessary to ensure approximation accuracy. As the real collected fingerprints may not be dense enough, virtual fingerprints are computed to fill in.

In Modellet, we adopt uniform sampling for simplicity. One example is shown in Fig. 4 where the VFPs distribute uniformly. The only parameter in generating the FP-Cloud is the sampling interval. In general, the VFPs should be as dense as possible to reflect the variation in signal strength. However, due to the possible imperfection of the signal propagation model (i.e., LDPL), the calculated virtual fingerprints have errors. Inserting overly dense virtual fingerprints may incur the side-effect of reduced robustness in searching for multiple nearest neighbours during the fingerprint matching phase. We will evaluate various sampling intervals in Section 7.2.

Through Section 4, we have discussed how to obtain a local model for any specific location of interest. Intuitively, we compute a radio map for each AP as shown in Fig. 6 (right). The final radio map is a union of the radio map of all APs, which is represented with FP-Cloud in Modellet. Having decided the positions of virtual fingerprints, their RSSs are calculated with local signal propagation models in the form of Eq. (2), for any particular VFP. Note that the list of APs in a virtual fingerprint is not necessarily a union of all the APs appearing in the database, but only those seen by the real fingerprints in proximity of the VFP.

6. DEVICE DIVERSITY HANDLING

Two collocated devices may receive significantly different signal strengths from the same AP due to the difference in hardware. Fig. 10 shows the histogram of RSS offsets measured by two collocated phones (HTC Titan and Nokia Lumia 900) at various locations. Specifically, the data is collected in a large shopping mall, where the two devices are put at various locations to measure the RSSs from surrounding APs. Fig. 10 is plotted by grouping the measurements by the two devices at the same location, and calculating the difference of the RSSs for the same BSSID. Fig. 10 is plotted based on data for all BSSIDs. One can see the offset value follows a Gaussian-like distribution centered around $-20dB$.

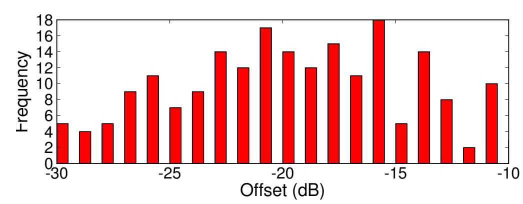

Figure 10: Offset between RSSs measured by two different devices.

Such a large gain offset can lead to bad localization results if the database is constructed with one device and directly used by another [13, 14, 29]. One solution is to measure the hardware gain offset between any pair of devices, which, however, is not scalable [29]. Authors in [13] evaluate existing methods, and concluded that the effectiveness of using RSS differences between observed APs in each fingerprint, instead of the absolute RSSs, which however significantly enlarges the dimension of fingerprints. In Modellet, we employ a light-weighted scheme during fingerprint matching as shown in Fig. 5. The idea is somewhat similar to [14] where Expectation Maximization (EM) is used to jointly estimate the location as well as device power level. However, the system architecture in [14] is different from ours where sniffers are deployed to locate a mobile client.

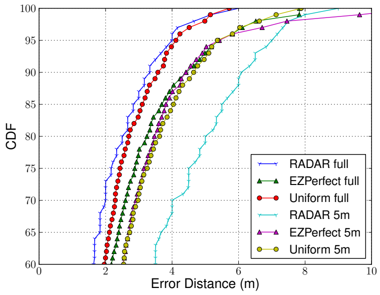

Figure 7: Comparisons of EZPerfect, RADAR, and Uniform.

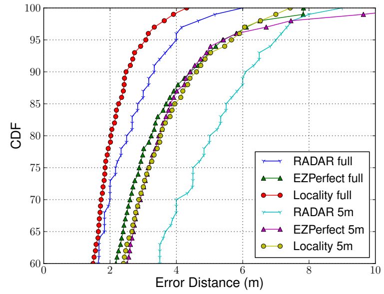

Figure 8: Comparison result of EZPerfect, RADAR, and Locality.

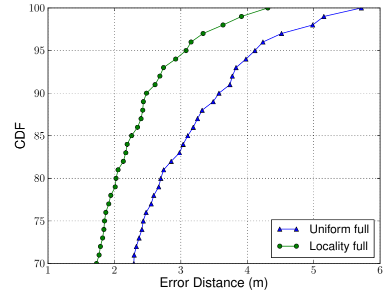

Figure 9: Comparison result of Uniform and Locality with full dataset.

Our scheme is detailed as follows. The conventional way of calculating the signal space distance Δ_{ij} between a pair of fingerprints $f_i = (r_1, r_2, \cdots, r_n)$ and $f_j = (s_1, s_2, \cdots, s_n)$ is

$$\Delta_{ij} = \sum_{k}^{n} |r_k - s_k| \tag{4}$$

We modify the calculation by adding a constant δ, such that $\Delta_{ij} = \sum_k^n |r_k - s_k + \delta|$. We vary δ in a certain range, and the gain offset o_{ij} between the two devices is estimated in Eq. (5) and the corresponding signal space distance Δ'_{ij} between f_i and f_j is calculated in Eq. (6).

$$o_{ij} = \arg\min_{\delta} \Delta'_{ij} \tag{5}$$

$$\Delta'_{ij} = \sum_{k}^{n} |r_k - s_k + o_{ij}| \tag{6}$$

In the offset estimation above, we simplify the transformation between a pair of devices (A and B) as a constant, i.e., $RSS_A = a \cdot RSS_B + \delta$ where $a = 1$. Actually, the measurement study in [29] found a is close to 1. It is therefore rare that two fingerprints measured at different locations by the same device have a constant offset between the RSSs of each observed AP, given APs deployed in various locations. We evaluate our solution with data collected by the two devices. The result is presented in Section 7.4.

7. EVALUATION

In this section, we evaluate the localization accuracy of Modellet, as well as other representative localization methods, with data collected from real, large scale deployments. We hope to reestablish a sense of achievable indoor localization accuracy using WiFi. Our key insights and understanding are summarized as follows:

- Modellet consistently outperforms the two baselines, RADAR and EZPerfect, in a small-scale office environment as well as large shopping malls and airports. The localization performance in office areas is consistent with what is reported in existing literature, while that in large venues is more contradictory. Possible reasons include uneven and inconsistent (on and off irregularly) AP deployment, with high transmission power (even could be heard several hundred of meters away).

- Generating dense VFPs for the FP-Cloud increases computation cost, but does not imply high localization accuracy. In fact, dense VFPs eliminate the robustness of fingerprint matching by finding the top few nearest neighbors. Thus, there is an optimal density which should be learnt offline.

- Modellet is not restricted to the LDPL model, but also others like the linear model. The LDPL model achieves a higher localization accuracy than the linear model, especially when the database is sparse.

- The device diversity problem significantly affects the localization accuracy. The scheme proposed in Section 6 handles the problem effectively with data collected by two devices from a large shopping mall.

7.1 Experiments Setup

We collect data with a cell phone from an office building in China and 13 large venues including shopping malls and airports (in the U.S. and Germany). The survey plan with a total of 221 fingerprints for the office building is shown in Fig. 11 where each red dot represents one fingerprint. Fig. 12 and Fig. 13 show the survey plan in two shopping malls. In this work, we collect data point by point for each venue. However, Modellet (as described in Section 3-6) is not tied up with any specific data collection approach. Other approaches like war-walking or crowdsourcing are also supported.

Table 1 shows the venue names along with the data coverage area, number of observed BSSIDs, and number of fingerprints. Most of the venues are in the U.S. with Alexa Shopping Mall located in Berlin, Germany. For these large venues, we have denser data coverage (3 $\sim$ 5m each) along the corridors and less for inner shop areas. Typically, for small sized inner shops, we have only one sample there, and a few scattered samples in large shops. The data along the corridors and in inner locations are collected separately. In this dataset, even though only one sample is taken for each location, data collection still consumes several hours for venues in Table 1.

We notice that in office buildings (or on a campus where most APs are deployed by one party), the APs are deployed more regularly to ensure uniform network coverage, whereas the APs in shopping malls or airports are placed less coordinated. Moreover, the APs' coverage in office areas is typically smaller to mitigate interference (e.g., 20 $\sim$ 30m) whereas the APs in those large venues have much larger coverage, some of which can even be heard hundreds of meters away.

7.2 Evaluation on An Office Area

The purpose of the evaluation on a relatively small office area (still over $3000m^2$) is two-fold: first, we want to examine a few settings like the density of the virtual fingerprints, and the usage of an LDPL model instead of a linear model; second, we want to evaluate the performance gain of Modellet against RADAR and

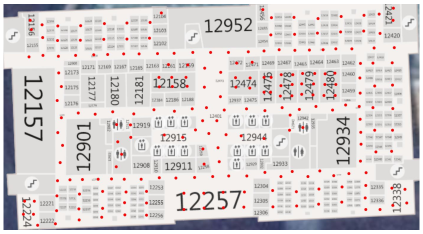

Figure 11: Data collection plan for an office building in Beijing, China.

Figure 12: Data collection plan for the Alexa Shopping Mall in Berlin, German.

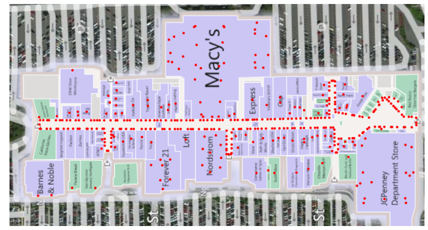

Figure 13: Data collection plan for the North Gate Mall in Seattle, U.S.

Venue Name	Area (m^2)	Bssids	FPs
Bellevue Square Mall	89216	1349	453
Redmond Town Center	29812	232	171
The Bravern	24244	675	148
Alexa Shopping Mall	35472	260	262
Commons At Federal Way	102172	398	329
Crossroads	129449	227	256
Los Angeles Intl Airport	127893	743	287
Marketplace at Factoria	135596	376	292
Northgate Mall	94810	749	403
Pacific Place	8619	258	97
South Hill Mall	237028	506	202
Supermall-Great Northwest	231188	440	632
Tacoma Mall	157491	749	455

Table 1: Basic statistics (spatial coverage, AP number and fingerprints collected) of the 13 venues and the survey data used in our evaluations.

EZPerfect in an office environment, which is the most common environment used by previous works.

Virtual fingerprint density: We vary the FP-Cloud VFP density from one per $1 \times 1m^2$ to one per $10 \times 10m^2$, and use all data from the small office area for experiments. To evaluate localization accuracy, we randomly partition the data into training (80%) and testing (20%). We conduct five batches and obtain the average performance, which is the default setting applied to all experiments hereafter.

We plot the localization error at 90%tile under various densities in Fig. 14. The error is defined as the 2D distance between the localization result and the groundtruth. Interestingly, we see that $5m$ (i.e., one sample per $5 \times 5m^2$) achieves the best accuracy. The reason is when virtual fingerprints becomes too dense, the robustness introduced by finding the top few nearest neighbours (in fingerprint matching in Fig.5) is eliminated. Imagine that, once the virtual fingerprints become extremely dense, the search process implicitly fallbacks to finding the top 1 nearest neighbour. We thus pick one per $5 \times 5m^2$ as our setting hereafter. Though it is hard to claim $5m$ is always the optimal setting, such a density makes adjacent virtual fingerprints differentiate enough from each other.

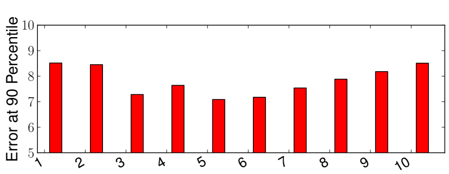

Figure 14: Performance at various VFP densities.

LDPL model vs. Linear model: We choose to use the LDPL model in Modellet. Modellet is actually not limited to the LDPL model. Other models like linear model can also be adopted. For instance, the linear model is defined as

$$RSS_{x,y} = \alpha \cdot x + \beta \cdot y + \gamma \quad (7)$$

where α, β, and γ are three AP dependent unknown parameters which can also be learnt from the calibration data. To implement the linear model, we simply replace the LDPL model with the linear model. Here we compare the localization accuracy of the LDPL model and the linear model at various data densities. For this purpose, after partitioning the whole dataset for training and testing, we do grid-based downsampling to emulate sparser data. Fig. 15 shows the comparison between using LDPL and linear models with full and downsampled datasets (with $10 \times 10m^2$ grid), respectively.

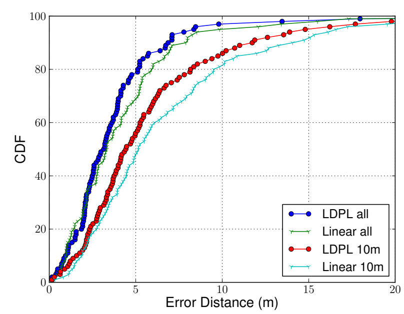

Figure 15: Localization accuracy comparison between LDPL and linear models.

In Fig. 15, one can see that the LDPL model outperforms the linear model at various data densities. The gap between the two gets larger at the sparse dataset. When the data is dense, filling in the blank using the LDPL model or the linear model does not make a significant difference. However, when data gets sparse, the LDPL model fits signal attenuation better than the linear model which assumes signal attenuates linearly.

Comparison Results: We carry out experiments comparing Modellet, RADAR, and EZPerfect in terms of localization accuracy. The result is shown in Fig. 16. One can see that EZPerfect outperforms RADAR on the dataset, which however has a long tail at high percentiles. Modellet achieves the best accuracy compared with RADAR and EZPerfect. The localization accuracy at 90%tile for the three are 6.4m, 8.3m, and 8.6m, respectively. The results presented here, as well as in our microbenchmarks, confirm the correctness of our implementation of RADAR and EZPerfect, as we can achieve reasonably good accuracy (sub 10m at 90%tile) in typical office buildings. The results are *consistent* with those

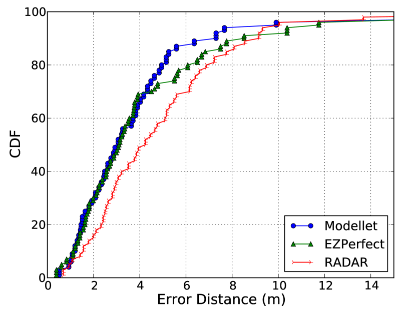

Figure 16: Localization accuracy evaluated based on data from an office building.

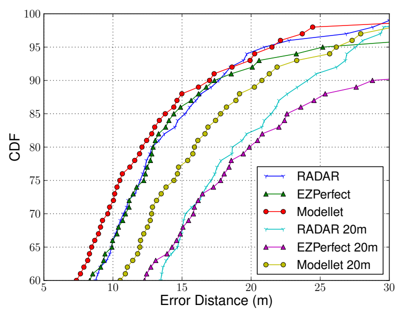

Figure 17: Localization accuracy evaluated based on data from Alexa Shopping Mall.

reported by most existing WiFi signal strength based indoor localization approaches.

7.3 Evaluations on Large Venues

We compare the localization accuracy of RADAR, EZPerfect, and Modellet using data collected from 13 large venues, listed in Table 1. As we have done before, we use the whole dataset as well as downsampled data for evaluation. As the original data is already sparse as shown in Fig. 12 and 13, we use grid size of 20m for downsampling. Before showing statistic result across all venues, we first show comparison result between RADAR, EZPerfect, and Modellet in Fig. 17 and Fig. 18, using data from the two venues shown in Fig. 12 and Fig. 13, respectively.

The first observation is that Modellet outperforms RADAR and EZPerfect at various data densities. The improvements are much larger than what we observed in our microbenchmarks or the small office area, especially when data is sparse. One reason is that the data density as well as environment become more diverse in such scenarios. As Modellet always takes advantage from both fingerprint-based and model-based approaches, the gain is enlarged under such conditions. The second observation is that localization accuracy becomes much worse in large venues than in a small office area. This contradicts with the results reported in existing literature. One important reason is that most existing works evaluate based on a well-maintained dataset collected in a lab area with ideal AP deployment.

Fig. 19 and Fig. 20 show the performance of RADAR, EZPerfect, and Modellet across the 13 venues. The x axis shows the prefixes of venue names. For each approach, we perform RADAR, EZPerfect, and Modellet with full and downsampled datasets, respectively. We show the localization errors at 50%tile and 90%tile in one stacked bar for each approach.

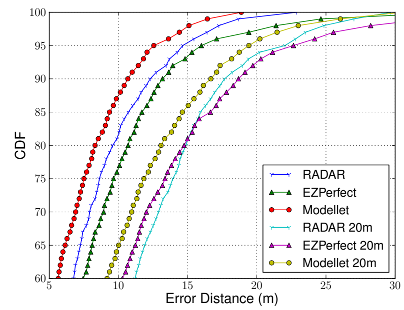

Figure 18: Localization accuracy evaluated based on data from the North Gate Mall.

We can see the localization errors vary significantly in different venues. The venue we show in Fig. 18 achieves the best localization accuracy with error at 90% close to 10m, while others range from 20m to 30m. For most venues, Modellet outperforms both RADAR and EZPerfect, or is as good as the better of the two. We do observe in 3 venues, i.e., South Hill Mall, Supermall, and Bellevue Square Mall, that EZPerfect or RADAR achieves the best (only at 90%tile). However, from Fig. 19, we can see the gaps between Modellet and the better of RADAR and EZPerfect in these 3 venues are small. On average, Modellet reduces errors at 50%tile and 90%tile by 0.77m and 1.14m, respectively, in comparison with the best of RADAR and EZPerfect over the 13 venues. Compared with the worst of the two, the mean reductions are 1.34m and 2.78m, respectively at 50%tile and 90%tile.

In Fig. 19, we can see that RADAR outperforms EZPerfect in 11 venues at 90%tile, and 12 venues at 50%tile. After downsampling the dataset with grid size 20m, we find that RADAR still achieves much better result than EZPerfect in most venues at 90%tile, shown in Fig. 20. However, at 50%tile, EZPerfect yields better result than RADAR in 6 venues, and similar result in another 2 venues. Note that this is partially consistent with our findings in our microbenchmark in Fig. 2 where EZPerfect works consistently better than RADAR when data is sparse. The reason is that when data becomes extremely sparse, the test cases collected in inner stores can cause bad localization due to a lack of appropriate models. In contrast, RADAR always maps the localization results to existing fingerprints, which thus eliminates producing tremendous large errors. Modellet still yields similar comparison results where the gain is larger than in Fig. 19. Modellet achieves the best performance in 12 venues, except for only one, i.e., The Bravern. Modellet reduces the errors at 50%tile and 90%tile by 0.9m and 1.44m, respectively, in comparison with the best in the two baselines, and 1.46m and 4.0m with the worst, respectively.

7.4 Handling Device Diversity Problem

We have discussed handling device diversity problem in Section 6. In our implementation, we set $\delta \in [-20, +20]$ dB. We collect data from a large shopping mall (i.e., the Pacific Place Mall) with two devices (i.e., HTC Titan and Nokia Lumia 900). We compare the localization performance with and without applying our light-weighted scheme handling the device diversity problem. The comparison result is shown in Fig. 21. One can see that as the gain offset between the two devices is as large as $20dB$. , localization result becomes extremely bad without handling the

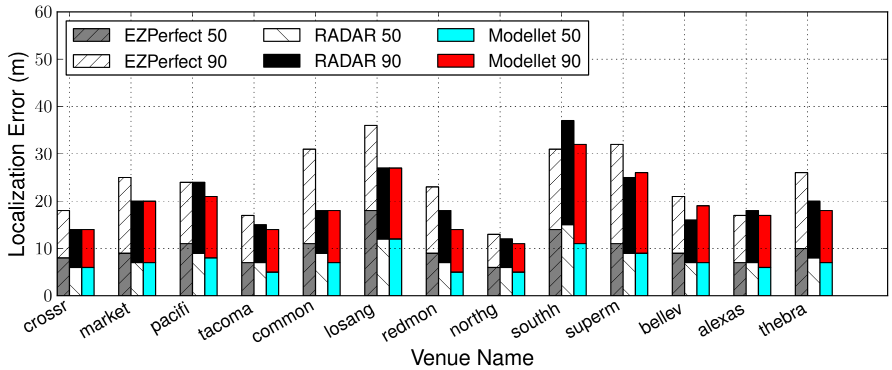

Figure 19: Localization accuracy for the 13 venues with full datasets.

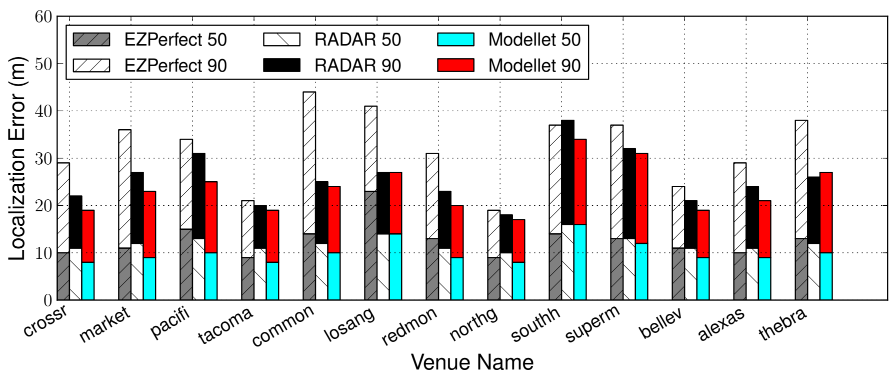

Figure 20: Localization accuracy for the 13 venues downsampled by 20m grid.

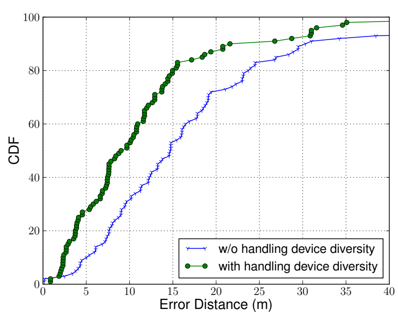

Figure 21: Localization accuracy before and after handling device diversity.

device diversity problem. In comparison, with our scheme, the localization accuracy is greatly and consistently improved by 40%.

8. DISCUSSIONS

Data Acquisition: Site survey needs to be done from time to time to update the database in order for facility changes like removing/replacing old APs and adding new APs. In this work, we assume the hiring of a site survey specialist to profile each venue for bootstrapping. With this method, we ensure a reasonably good initial user experience. Further more, we obtain a database collected by a standard device, which make it easier to deal with the device diversity issue as explained in Section 6. After bootstrapping, we adopt crowdsourcing to update the database. In practice, crowdsourcing can be carried out leveraging people already in the venue of interest. For instance, shop owners have incentive to help data collection in order to provide a better in-store user experience. We thus make the localization database maintainance scalable.

Power Adaptation Reality: Modern APs feature the capability of *adaptive power control*, where an AP automatically changes its power level [1]. If the power changes frequently (e.g., every 10min) in a random fashion, the existing models will be impaired, leading to unpredictable localization result for all WiFi RSS based localization approaches. However, according to [1], the main purpose for power adaptation is to ensure coverage while reducing interference among neighboring APs. Therefore, as long as no neighboring AP fails, the power level for each AP remains stable after convergence. We are also aware that this capability is especially designed for enterprise networks where APs work collaboratively. In large shopping malls or airports, a large fraction of APs are deployed by third party shop owners. The transmit power of these APs are typically stable, which is confirmed with our collected data.

Dealing with Large Errors: For a localization service, large localization errors are harmful to the user experience. In practice, large errors could be caused by various reasons, e.g., a bad WiFi scan during site survey or user query. One opportunity to eliminate large errors is to perform multiple scans at each sampling location either for site survey or user localization. For localization, the result averaged over multiple scans typically outperforms that with a single scan [40]. Another opportunity is to leverage the inertial sensors to continuously track the user, and thus correct big errors with filtering such as [22]. However, one drawback of tracking schemes is the increased battery consumption by sensors.

Adding Map Information: A few studies [17, 21] show the potential of adding map information to improve localization accuracy. While such accurate information is usually missing in reality, Modellet can easily incorporate the map information, if they are indeed available, by lowering the weights of real fingerprints intervened by walls.

Cost of FP-Cloud: The cost we pay is the need to store a large number of virtual fingerprints in the FP-Cloud. It will lead to larger storage and memory consumption, and longer downloading time. As the client can cache the database locally, only incremental cost need to be paid when the database is updated. Moreover, the database can be compressed significantly as a large amount of space is for storing duplicated BSSIDs ($\sim 10\%$ of the original size after compression in zip format in our empirical evaluation). Therefore, such extra storage cost is still affordable. Generating FP-Cloud also requires high computation power, especially for large venues. First of all, the complexity is mainly determined by the density of VFP, and thus is controllable. Moreover, the models are trained offline in the cloud which thus is less a concern.

Extension to Multi-story Buildings: Floor detection is a crucial yet non-trivial indoor localization problem, especially in large shopping malls where large open areas exist. Generally, floor detection is a locality decision problem from a 3D perspective. In this paper we do not touch floor detection due to space limits. However, our experiments confirm that Modellet is still very effective for floor detection. It achieves over 95% accuracy on average.

9. RELATED WORK

Early indoor localization projects use dedicated location devices, such as Active Badge [36] and Cricket [30]. Later, significant effort is spent on ubiquitous, less expensive indoor localization services, including infrastructure independent (Geo-magnetic field, IMU sensors, etc.) [10, 22, 31, 34], infrastructure dependent which further consists of leveraging existing infrastructure (WiFi, FM, etc.) [4, 5, 8, 9, 15, 17, 20, 39–41], and those deploying new infrastructure (acoustic, LED, etc.) [16, 25, 27, 28, 37]. In this paper, we focus on WiFi based indoor localization, for its wide availability, no extra deployment cost, reasonable accuracy, and readiness to apply to mobile devices.

Among existing work, tremendous effort has been devoted to investigating better WiFi localization algorithms. Most existing WiFi based approaches can be divided into two categories: *fingerprint-based* and *model-based*.

Fingerprint-based techniques: The category of fingerprint-based approaches is pioneered by RADAR [5], and followed by numerous improvement algorithms [20, 40]. By and large, they can be classified into deterministic approaches (e.g., [5, 7, 12, 19]) or stochastic approaches (e.g., [20, 40]). The former directly calculates the distance between fingerprints and finds the most matched one or multiple fingerprints. The latter computes the likelihood of a query fingerprint against those in the database that also contain statistical information of fingerprints. Interpolation schemes were also proposed to match the query fingerprint to the database including interpolated fingerprints [7, 19]. Recent advancement has shown that sub-meter accuracy can be achieved by exploring physic layer information [32] or ranging between devices in proximity [24, 28]. In general, a high quality database is required to obtain high localization accuracy, as shown by extensive experiments with multiple algorithms [6, 12]. Thus, the major drawback of fingerprint-based approaches is the excessive time and labor it takes to construct the database via site survey. A few recent studies [22, 31, 33, 38] demonstrate the possibility of leveraging crowdsourcing to reduce the burden of site survey. However, designing a sustainable incentive mechanism of crowdsourcing remains a challenge.

Model-based techniques: Schemes in this category use a RF propagation model to derive RSS at various locations. The log-distance path loss (LDPL) model is a widely used model [9, 11, 15, 23]. Typically, a few measurements are required to train the model for each AP. In TIX [15], each AP is assumed to be able to sense APs nearby, and therefore, no extra calibration is required. EZ relieves the assumption, [9] requires only minimum labelled fingerprints along with a large amount of unlabelled fingerprints, and is able to achieve reasonable accuracy. Later in [28], it is shown that, by having data all labelled in EZ, the accuracy can further be improved (this scheme is called EZPerfect). When precise building structure information is known, it is possible to adopt more sophisticated ray-tracing techniques, as shown in ARIADNE [17]. Recently, the authors of [35] have evaluated a few model-based schemes including [11, 15, 23] on a moderate-scaled testbed, and concluded that the achieved accuracy is much worse than reported under realistic conditions.

Summary of differences: So far, most effort has been spent on improving localization accuracy upon a well maintained dataset. Less attention has been paid to intrinsic properties of practically collected location databases, which leads to a mismatch between the reported localization accuracy and reality as implied in [35]. In this paper, we propose Modellet which augments the radio map with virtual fingerprints. Our work differentiates from existing work in several ways. We show that such properties, i.e., data density and environment diversities, significantly impact localization accuracy. We also show that a single approach (fingerprint-based or model-based) or simple hybrid cannot address such issues. Finally, we propose Modellet to adapt between fingerprint-based and model-based approaches, driven by the data density and environment diversities.

10. CONCLUSION AND FUTURE WORK

In this paper, we have identified the data density and environment diversities problems that arise from real-world WiFi-based indoor localization system deployments. We have designed Modellet that attacks the problem by constructing a location database that best approximates the actual radio map based on the new concepts of the supporting set and fingerprint-cloud. We evaluate and compare Modellet and existing representative indoor localization systems, namely RADAR and EZPerfect, with data collected at an office building and 13 large venues. The results confirm the effectiveness of Modellet and also reveal the inadequate performance of existing systems in real-world deployment.

As to future work, we will look into the database maintenance problem, which is critical to provide long running indoor localization services.

11. ACKNOWLEDGMENTS

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12. REFERENCES

[1] Cisco wireless lan controller configuration guide, release 4.1.

[2] Googlers Talk Indoor Maps For 40 Minutes. `http://www.webpronews.com/googlers-talk-\\indoor-maps-for-40-minutes-video-2013-05`.

[3] IN-Location Alliance. `http://www.in-location-alliance.com/`.

[4] M. Azizyan, I. Constandache, and R. Roy Choudhury. Surroundsense: mobile phone localization via ambience fingerprinting. In *Mobicom*, pages 261–272. ACM, 2009.

[5] P. Bahl and V. N. Padmanabhan. Radar: An in-building rf-based user location and tracking system. In *INFOCOM*, volume 2, pages 775–784. Ieee, 2000.

[6] G. Chandrasekaran, M. Ergin, J. Yang, S. Liu, Y. Chen, M. Gruteser, and R. Martin. Empirical evaluation of the limits on localization using signal strength. In *SECON*, pages 1–9, 2009.

[7] M. Y. Chen, T. Sohn, D. Chmelev, D. Haehnel, J. Hightower, J. Hughes, A. LaMarca, F. Potter, I. Smith, and A. Varshavsky. Practical metropolitan-scale positioning for gsm phones. In *UbiComp*, pages 225–242. Springer, 2006.

[8] Y. Chen, D. Lymberopoulos, J. Liu, and B. Priyantha. Fm-based indoor localization. In *Mobisys*, pages 169–182. ACM, 2012.

[9] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan. Indoor localization without the pain. In *Mobicom*, pages 173–184. ACM, 2010.

[10] J. Chung, M. Donahoe, C. Schmandt, I.-J. Kim, P. Razavai, and M. Wiseman. Indoor location sensing using geo-magnetism. *MobiSys*, page 141, 2011.

[11] L. F. M. de Moraes and B. A. A. Nunes. Calibration-free wlan location system based on dynamic mapping of signal strength. In *Proceedings of the 4th ACM international workshop on Mobility management and wireless access*, pages 92–99. ACM, 2006.

[12] E. Elnahrawy, X. Li, and R. Martin. The limits of localization using signal strength: a comparative study. In *SECON*, pages 406–414, 2004.

[13] S.-h. Fang, C.-h. Wang, S.-m. Chiou, and P. Lin. Calibration-free Approaches for Robust Wi-Fi Positioning Against Device Diversity : A Performance Comparison. *VTC Spring*, 2012.

[14] A. Goswami, L. E. Ortiz, and S. R. Das. Wigem: a learning-based approach for indoor localization. In *COnference on emerging Networking EXperiments and Technologies*, page 3. ACM, 2011.

[15] Y. Gwon and R. Jain. Error Characteristics and Calibration-free Techniques for Wireless LAN-based Location Estimation. *MobiWac*, pages 2–9, 2004.

[16] P. Hu, L. Li, C. Peng, G. Shen, and F. Zhao. Pharos : Enable Physical Analytics through Visible Light based Indoor Localization. *HotNets*, 2013.

[17] Y. Ji, S. Biaz, S. Pandey, and P. Agrawal. Ariadne: a dynamic indoor signal map construction and localization system. In *Mobisys*, pages 151–164. ACM, 2006.

[18] N. Kodippili and D. Dias. Integration of fingerprinting and trilateration techniques for improved indoor localization. In *WOCN*, pages 1–6. IEEE, 2010.

[19] P. Krishnan, A. Krishnakumar, W.-H. Ju, C. Mallows, and S. Gamt. A system for lease: Location estimation assisted by stationary emitters for indoor rf wireless networks. In *INFOCOM*, volume 2, pages 1001–1011. IEEE, 2004.

[20] J. Krumm and J. Platt. Minimizing calibration efforts for an indoor 802.11 device location measurement system. *MSR-TR-2003-82*, 2003.

[21] B. Li, A. G. Dempster, C. Rizos, and J. Barnes. Hybrid method for localization using WLAN. *Spatial Sciences Conference*, 2005.

[22] F. Li, C. Zhao, G. Ding, J. Gong, C. Liu, and F. Zhao. A reliable and accurate indoor localization method using phone inertial sensors. In *Ubicomp*, pages 421–430. ACM, 2012.

[23] H. Lim, L.-c. Kung, J. C. Hou, and H. Luo. Zero-Configuration , Robust Indoor Localization : Theory and Experimentation. *INFOCOM*, pages 1–13, 2005.

[24] H. Liu, Y. Gan, J. Yang, S. Sidhom, Y. Wang, Y. Chen, and F. Ye. Push the limit of wifi based localization for smartphones. In *Mobicom*, pages 305–316. ACM, 2012.

[25] K. Liu, X. Liu, and X. Li. Guoguo : Enabling Fine-grained Indoor Localization via Smartphone Categories and Subject Descriptors. *Mobisys*, 2013.

[26] D. Madigan, E. Einahrawy, R. P. Martin, W.-H. Ju, P. Krishnan, and A. Krishnakumar. Bayesian indoor positioning systems. In *INFOCOM 2005*, volume 2, pages 1217–1227. IEEE, 2005.

[27] A. Matic, A. Papliatseyeu, V. Osmani, and O. Mayora-Ibarra. Tuning to your position: Fm radio based indoor localization with spontaneous recalibration. In *PerCom*, pages 153–161. IEEE, 2010.

[28] R. Nandakumar, K. K. Chintalapudi, and V. N. Padmanabhan. Centaur : Locating Devices in an Office Environment. In *Mobicom*, 2012.

[29] J.-g. Park, D. Curtis, and J. Ledlie. Implications of Device Diversity for Organic Localization. *INFOCOM*, pages 3182–3190, 2011.

[30] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan. The cricket location-support system. In *Mobicom*, pages 32–43. ACM, 2000.

[31] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen. Zee: Zero-effort crowdsourcing for indoor localization. In *Mobicom*, pages 293–304. ACM, 2012.

[32] S. Sen, B. Radunovic, R. R. Choudhury, and T. Minka. You are facing the mona lisa: spot localization using phy layer information. In *Mobisys*, pages 183–196. ACM, 2012.

[33] G. Shen, Z. Chen, P. Zhang, T. Moscibroda, and Y. Zhang. Walkie-Markie : Indoor Pathway Mapping Made Easy. *NSDI*, 2013.

[34] S. P. Tarzia, P. a. Dinda, R. P. Dick, and G. Memik. Indoor localization without infrastructure using the acoustic background spectrum. *MobiSys*, 2011.

[35] D. Turner, S. Savage, and A. C. Snoeren. On the empirical performance of self-calibrating wifi location systems. In *LCN*, pages 76–84. IEEE, 2011.

[36] R. Want, A. Hopper, V. Falcão, and J. Gibbons. The active badge location system. *TOIS*, 10(1):91–102, 1992.

[37] J. Xiong and K. Jamieson. ArrayTrack : A Fine-Grained Indoor Location System. *NSDI*, (279976):71–84, 2013.

[38] Z. Yang, C. Wu, and Y. Liu. Locating in fingerprint space: wireless indoor localization with little human intervention. In *Mobicom*, pages 269–280. ACM, 2012.

[39] S. Yoon, K. Lee, and I. Rhee. Fm-based indoor localization via automatic fingerprint db construction and matching. In *Mobisys*, pages 207–220. ACM, 2013.

[40] M. Youssef and A. Agrawala. The horus wlan location determination system. *Mobisys*, 2005.

[41] M. A. Youssef, A. Agrawala, and A. Udaya Shankar. Wlan location determination via clustering and probability distributions. In *PerCom*, pages 143–150. IEEE, 2003.